

**RESEARCHING THE EFFECTIVENESS OF BEST
PRACTICE ADVISORIES WITHIN CLINICAL
DECISION SUPPORT SYSTEMS AT BOULDER
COMMUNITY HEALTH****AUTHORS**

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INTRODUCTION

Michael Jefferies, Boulder Community Health's Chief Information Officer and an alumnus of the Health Administration graduate program at the University of Colorado Denver, graciously offered to precept this field study project. Initially, we discussed various potential projects, from Epic implementation efforts around Telehealth and Qlik to joint ventures with the University of Colorado Health Systems and the Sports Medicine Program at the University of Colorado. After discussions, ultimately, we decided that Clinical Decision Support Systems (CDSS) presented an area of need for Boulder Community Health and aligned with my information technology interests. More specifically, Best Practice Advisories and Alerts (BPAs) required a granular level of investigation to review their effectiveness on physician workflow.

Before discussing background information, let us address this question: Why are Clinical Decision Support Systems interesting? When the first versions of Electronic Health Records (EHRs) appeared in the 1960s, these systems primarily functioned in a rudimentary fashion to adequately store and retrieve medical documentation and clinical information. However, EHRs in the modern market is universally adopted and garner immeasurable responsibility. These systems are critical platforms for healthcare organizations that provide vastly complex layers of data storage and information, customized solutions for providers and patients, an immense level of necessary integration into daily operations, mitigation of medical liability, and so much more. As healthcare tools like EHRs and CDSS progress, we must recognize the exciting potential behind the technological advancements in this realm. In our opinion, healthcare currently sits in its infancy with technological integration, and we find artificial intelligence in concert with Clinical Decision Support Systems to be particularly thought-provoking.

CDSS has a high-value role in modern medicine, providing evidence-based clinical guidelines for the diagnosis and treatment of patients. As healthcare continues to grow in complexity, the demand for physicians also becomes increasingly unsustainable without CDSS. Robust and highly efficient CDSS improve the cohesion between providers and information technologies while effectively empowering providers to navigate the ever-accelerating healthcare environment. Despite these promising aspects of

CDSS, integrating these systems requires a significant level of resources, strategy, and oversight. This holds across all healthcare organizations, from small private practices to entire health systems such as Boulder Community Health.

PROJECT CONTEXT

In October 2019, Boulder Community Health transitioned from Meditech to Epic Systems as their primary EHR. The massive overhaul of Meditech and the long-overdue transition of their Information Technology Systems created unforeseen challenges. One of these challenges was the overabundance of Best Practice Advisory Alerts generated by Boulder Community Health's CDSS within Epic. These alerts are essential for physicians and other providers to make accurate clinical decisions, reduce redundant inefficiencies, and mitigate potential liability or poor outcomes. However, issues arise when high levels of unnecessary alerts flood the technological systems providers use. Ultimately the increased quantity of the alerts impedes physician workflow and creates 'alert fatigue.'

Michael Jefferies tasked us with researching the effectiveness of existing BPAs and eliminating less effective alerts to improve physician workflow. Based on the data, we worked to identify specific alerts that are either overridden at high rates or are incorrectly generated to be suppressed. Based on current and past data research, the current state was analyzed, and recommendations were made for a formal review in a weekly iterative fashion.

RESEARCH APPROACH

In cooperation with David Whitting (MD & Chief Medical Information Officer), Adam Crabtree (Pharmacist & Clinical Informaticist), and other information system personnel, we provided a comprehensive analysis and reported on this issue. Dr. Whitting advised us to focus on Medication Alerts (a subcategory of BPAs) before moving on to other data sets. This portion of the report will discuss a current state and retrospective analysis, key outcome measures, how the issue was approached, improvement efforts implemented, and recommendations for continuous improvement efforts.

CURRENT STATE AND RETROSPECTIVE ANALYSIS

The medication alerts have a unique data collection system and generate 'optimization reports' based on the time-series data. These reports categorically parse the data into various categories such as Phases of Care, Warning Types (i.e., drug-drug interactions), Dose Thresholds, etc. At this point, we began to collect retrospective data to understand the current state of the medication alerts. Starting with October 2019, when the Epic EHR was implemented, then taking three-month (quarterly) increments of data. Each month of data was compared and reviewed for the progress made since the inception of the new EHR. (i.e., 10/2019, 1/2020, 4/2020, 7/2020, 10/2020, 1/2021, & 3/2021)

At this point, a variety of important metrics were compared for each month. We created new data tables (See Appendix Tables 1 & 2) to review potentially beneficial research metrics to translate this data into digestible visual analytics. The most straightforward metric, the number of warnings, in Figure 1 of the Appendix demonstrates how tenuous the initial Epic launch was in October 2019. After launch, there was a 75.5% reduction (10,383 to 2,548 unfiltered warnings) within the first three months.

Despite this massive reduction in warnings initially, physicians and other clinicians communicated that their workflow continues to be stifled by unnecessary warnings. Over the past year, Dr. Whitling and Adam Crabtree have reviewed the data and suppressed various alerts. However, the overall number of alerts remained consistent and is showing a trend of increasing. (See Appendix Figure 2) Notably, this shows that implementation efforts overall have a minimal effect on the total number of alerts and indicates that the CDSS is likely creating new alerts. With the consistent creation of new alerts within the CDSS, the root cause has not been addressed. This will be discussed further in a later section.

The override rates across the system are another metric that reinforces this logic. Figure 3 in the Appendix shows that clinicians are being flooded with excessive warnings that are typically overridden about 80-86% of the time. When reviewing the categories of medication alerts, it is apparent that Drug-Allergy Alerts have the lowest override rates and provide the highest value of warning types. When Drug-Allergy Alerts are omitted from the data, the overall override rates across the system have less variation and increase significantly to a range of 91-93%. (See Appendix Figure 4) At this point in the analysis, we concluded that Boulder Community Health should agree upon a target level of overrides to occur. The literature review in this report reinforces this decision.

KEY OUTCOME MEASURES

While conducting the current state analysis, two metrics were identified as the Key Outcome Measures: Unfiltered Warnings Per 100 Orders & Overridden Warnings Per 100 Orders. These metrics accurately capture implementation efforts, account for census variation, and show the relative scale of warnings occurring per order in each data set. Also, the first metric identifies “Unfiltered Warnings,” which specifically have not been suppressed or ‘filtered’ previously. Based on these unique distinctions, we proceeded to monitor our progress based on these metrics. (See Appendix Figures 5 & 6)

METHODOLOGY

After an initial current state analysis, we were tasked with researching and analyzing raw data reports to identify highly impactful interactions. Again, these interactions were

specific to medication alerts. After identifying these interactions, we would discuss our findings with Adam Crabtree, whose background as a pharmacist would critique our findings and filter out potential implementation opportunities. The optimization reports categorically assigned the data into a “breakdown section.” From the breakdown section, we identified the most impactful categories of alerts firing and created a formal review of findings. An example of our initial finding from the formal review is given next.

Our findings based on the data were “The categories of Drug-Drug, Drug-Disease, Dose, Pregnancy, and Lactation account for 50% of the total unfiltered warnings, with an average overall override rate of 97.52%. (including pharmacists and infectious disease providers) More importantly, these categories account for 59% of the total number of overrides.” The action item was “Should we primarily focus on these categories?” Adam’s input was, “Yes. However, some of these categories present more challenging pathways for suppression.”

After Adam confirmed that our efforts should primarily focus on these categories (Drug-Drug, Drug-Disease, Dose, Pregnancy, and Lactation alerts), we began reviewing each of these data sets to identify the most frequent medication alerts. In our approach, we cross-referenced multiple variables, and the medications that frequently fired across multiple variables were reviewed for suppression. This intensive process required a highly granular level of detail. We will not discuss the specific medications identified for brevity, but please refer to Figure 7 in the appendix to reference a detailed example.

Fortunately, we were able to work each week iteratively and make a series of impactful implementation efforts. My analysis was structured from an objective, quantifiable perspective; we did not attempt to base my findings on clinical information or research on pharmacology.

IMPROVEMENT EFFORTS IMPLEMENTED

After performing a granular review and research-intensive process of the medication alert data, our team identified impactful suppression for specific medication alerts. The inner workings of how these alerts were suppressed were left to Adam Crabtree and other IT staff. Table 1 lists the specific alerts suppressed at the system level, reducing these alerts for all types of physicians.

After these findings were implemented and suppressed, we reviewed our Key Outcome Measures. Identifying and suppressing big offenders that directly impacted physicians across all specialties saw about a 3% decrease system-wide in medication alerts without jeopardizing meaningful notifications. (See Appendix Figure 6 from January 2021 to March 2021) This successful decrease is noteworthy. However, prior to this field study, alerts across the system

continue to grow each quarter. Overall, growth in alerts reinforces that our suppression efforts do not effectively address the root cause of alert growth at Boulder Community Health.

1.	1600000053 Duplicate med, duplicate therapy
2.	30410026 Duplicate therapy POA order set
3.	245 dose warnings (standing orders newborn)
4.	30404065 pregnancy suppressed (post-delivery)
5.	30404027 pregnancy suppressed (antepartum)
6.	30404279 OSQ pregnancy
7.	Suppressed duplicate BZD injectables (typically only fire with versed and prn diazepam, not the same scenario)
8.	Suppressed duplicate NSAID with Warfarin in FIS settings FIS
9.	Suppressed SSRI and anticoagulants FIS
10.	Suppressed Epinephrine & Beta blockers (Epinephrine is only a PRN medication for emergency use) FIS
11.	Opioid Analgesics- IR (with all antitussive opiates) [746]
12.	Phenothiazines [230]
13.	Bicarbonates [65]
14.	Antipsychotics (excluding select aripiprazole formulations) [968]
15.	Phase of Care → Anesthesia Intraoperative x Phase II/On Unit
16.	Order Sets → Max Dosage Threshold review

IDENTIFYING ROOT CAUSE

Our suppression work did not impact the growing total number of alerts and the high override rates. When looking at Figures 2 & 3 in the appendix, these metrics show negligible differences in the month of March 2021 compared to previous data. This is an important finding for the final recommendations and continuous improvement.

One potential contribution to the overall growth in alerts is that Boulder Community Health is still developing and optimizing its EHR and consistently adds Order Sets and Panels for physicians. However, by adding new medication Order Sets and Panels, downstream growth in redundant alerts is seen across the entire system. Although the intention of adding Order Sets and Panels for physicians is to improve workflow efficiency, the positive impacts are negated by the overall increase in alerts for all clinicians, including pharmacists and infectious disease providers.

One potential contributor to the negligible effect in override rates could be due to “Alert Fatigue.” This term is commonly used in the recent research literature and is a growing study area for BPAs. According to Afaq et al., (2019), “Alert fatigue is one reason for high override rates.

Alert fatigue causes physicians to become desensitized to safety alerts and potentially ignore pertinent and useful information.” Perhaps, this is attributed to the logic that once alert fatigue is present, small decreases in the relative volume of alerts (such as the 3% system-wide decrease we noted) are overlooked, and physicians continue to override alerts routinely. However, the literature review provides more insight on methods to combat the underlying barriers to continuous improvement in this area.

LITERATURE REVIEW

To keep this literature review concise, we have summarized significant conclusions from recent research studies and why these conclusions are relevant findings for this report in Table 2.

Direct Research Quote	Noteworthy Reasoning
<ul style="list-style-type: none"> “...a high override alert rate has been found, with 49% to 69% of medication alerts are overridden by prescribers.” “The physicians experiencing traditional alerts ignored up to 87.8%, while the physicians with “on-demand” alerts ignored only 24.4%.”¹ 	<ul style="list-style-type: none"> This study claims that 49% to 69% are considered high override rates. The new target goal for BCH could be 70%.
<ul style="list-style-type: none"> “Examples of quantitative research supporting the overload explanation include studies finding that override rates decreased overall after irrelevant alerts were discontinued.” “A pre-post study showed that after irrelevant alerts were retired, pharmacist alert override rates decreased from 93% to 86%” “... among repeated drug alerts, if the clinician overrode the first instance, the chance of overriding subsequent instances was 99.9%, whereas if the first instance was accepted, the chance of overriding subsequent instances was 58.4%.” (*This is specific to Drug-Drug and Drug-Allergy Interactions) “An influential systematic review of CDSS override rates 	<ul style="list-style-type: none"> Reinforces that our work this semester was meaningful. Pharmacist suppression implementation should coincide. Reinforces that User-filtered Warnings are a great tool for this reason. Suggests “Total number of alerts” is not a KOM for workflow impact. Override rates are not necessarily related to caseload or RVUs. Patient repeats are a viable target.

¹ Afaq, H., Mukundan, S., Zia, S., Escano, A. K., Lear, R., & Washington, C. (2019). *Providers' Perception of Alert Fatigue After Implementation of User-Filtered Warnings*. Pharmacotherapy And Outcomes Science Publications.

https://scholarscompass.vcu.edu/cgi/viewcontent.cgi?article=1025&context=phar_pubs.

<p>noted that across studies there was no evidence of a relationship between alert volume and percentage overridden.”</p> <ul style="list-style-type: none"> • “Override rates were not linked to indicators of general workloads, such as the number of patients seen and the number of encounters.” • “Approaches to reduce the numbers of within-patient repeats could be a promising target for reducing alert override rates and alert fatigue.”² 	
<ul style="list-style-type: none"> • “Suggested alert management strategies include prioritizing alerts, developing sophisticated alerts, customizing commercially available alerts, and including end-user opinion in alert selection.”³ 	<ul style="list-style-type: none"> • Noteworthy strategies for alert management, especially end-user interoperability.

RECOMMENDATIONS AND CONTINUOUS IMPROVEMENT

After completing this analysis, we have four remaining suggestions for continuous improvement on reducing BPAs at Boulder Community Health. The final recommendation would require the most resources. For this reason, we have created an action plan, a pros/cons section, and an end-user example to illustrate why UFW can be effective in areas where system-wide suppression is not. (See Appendix Diagram 1)

Implement the same suppression for pharmacists as well. Follow up with Adam Crabtree to ensure that all of the work done to suppress physician alerts is also approved for pharmacists. This will reduce communication redundancy and improve workflow across that department. Our other report describes unique pharmacy-specific drug interactions indicated as “severe interactions.” These have been flagged and included in a supplemental document for follow-up with those leaders.

Agree on a targeted goal for override rates. Research suggests that an annual goal for Boulder Community Health could be decreasing override rates to 70% across all providers. This is a tangible starting goal, not an ideal optimized goal.

Consider the effectiveness of reviewing and eliminating alerts for patient repeats. If a physician has prescribed a similar medication or treatment for a specific patient, they are likely aware of the risks and benefits associated with that treatment path.

System-wide extensive promotion of the User-Filtered Warnings (UFW) Tool. According to Adam, the next phase of system-wide suppression will require granular and specific use cases to identify changes effectively. This indicates that little progress will be made with the current level of resources attributed to this area. Based on current utilization data, Adam and I recognized the underutilization of the user-filtered tool. With executive leadership’s support and endorsement, this could be an excellent opportunity for the provider-education to increase the utilization of this tool. Buy-in from executive leadership and physician leadership will be critical to realizing the full effects of UFW. Afaq et al. (2019) found significant decreases in the overrides rates when utilizing the UFW tool in a five-hospital system, “In addition to the total number of alerts, the override rates decreased as well by 11.3% after the implementation of UFW.” Afaq et al. (2019) also reinforced that lack of awareness could be attributed to low utilization: “Low utilization of UFW may be due to a lack of awareness of this function as communication with physicians is a known limitation within the health system.” Quite simply, this is an excellent solution to efficiently and effectively combat alert fatigue and unnecessary, burdensome alerts.

CONCLUSION

This project relied heavily on data analysis, data-driven decision-making, and systems thinking. Fortunately, we were allowed to dive right into raw data and impact implementation within the first few weeks. We genuinely enjoyed observing the tangible results from our work in such a short timeframe and gaining real-world exposure with CDSS/BPAs. Our most valuable take-away from this experience is to consider systems thinking by addressing the root cause of a problem and considering downstream/upstream influences for the most effective utilization of resources. We hope that our findings will propel further success in reducing alert fatigue and the stifling number of alerts that interrupt clinical workflow.

² Ancker, J. S., Edwards, A., Nosal, S., Hauser, D., Mauer, E., & Kaushal, R. (2017, April 10). *Effects of workload, work complexity, and repeated alerts on alert fatigue in a clinical decision support system.* BMC medical informatics and decision making. <https://www.ncbi.nlm.nih.gov/pmc/articles/PMC5387195/>.

³ Kane-Gill, S. L., O’Connor, M. F., Rothschild, J. M., Selby, N. M., McLean, B., Bonafide, C. P., ... Winters, B. D. (2017). *Technologic*

Distractions (Part 1): Summary of Approaches to Manage Alert Quantity With Intent to Reduce Alert Fatigue and Suggestions for Alert Fatigue Metrics, 45(9), 1481–1488. <https://doi.org/10.1097/ccm.0000000000002580>

APPENDIX TABLES AND FIGURES

TABLE 1: QUARTERLY OPTIMIZATION DATA IN TIMESERIES

Quarterly Increment	Unfiltered Warnings Per 100 Orders	Overridden Warnings Per 100 Orders	Number of Unfiltered Warnings	Number of Overridden Warnings	Overall Override Rate	Override Rate: Provider Interaction
October 2019	55.8	50.2	10,383	9,326	90.6	89.3
January 2020	16.7	13.4	2,367	1,902	82.7	78
April 2020	17.9	15.1	1,122	946	85.6	81.6
July 2020	17.6	14.3	2,274	1,859	84	78.8
October 2020	17.9	14.8	2,717	2,242	85.5	79.5
January 2021	19.3	15.6	2,334	1,886	82.7	79.4
March 2021	16.7	13.9	2,548	2,123	86.3	80.1

TABLE 2: CATEGORIES OF MEDICATION WARNINGS BY MONTHLY INCREMENTS.^a

Warning Type Category	October 2019	January 2020	April 2020	July 2020	October 2020	January 2021	March 2021
Drug-Drug	52.5	13.4	18.7	20.1	22.3	23.7	26.9
Drug-Allergy	9.3	23.2	15.2	23	21.5	21.4	20.6
Duplicate Therapy	9.3	25	24.3	21	21.3	20.1	18.9
Drug-Disease	17.7	9.4	14.3	13.8	15.1	16.1	17.8
Duplicate Medication	4.4	14.4	13.1	11	8.8	8.3	6.9
Dose	3.1	5.9	6.8	4	4.6	5	3.8
Pregnancy	3.5	8.5	4.5	5.8	3.4	3	3.7
Lactation	0.2	0.3	3.2	1.3	3.1	0.6	1.3

^a Each 'month' of data is representative of the first weeks' worth of data within that month due to the sheer size of the data files.

FIGURE 1. THE NUMBER OF BPA WARNINGS INCLUDING EPIC LAUNCH IN OCTOBER 2019

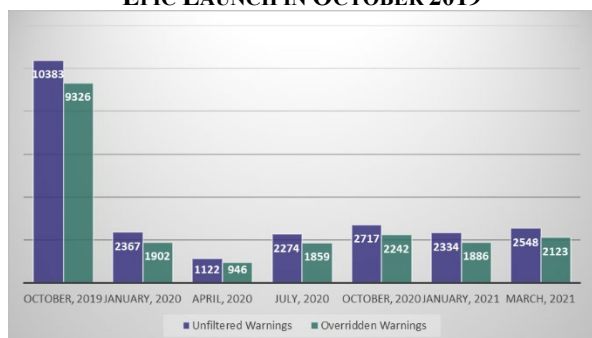


FIGURE 2. THE NUMBER OF BPA WARNINGS OMITTING EPIC LAUNCH



FIGURE 3. TOTAL OVERRIDE RATES OF ALL BPA WARNINGS, FOR ALL CLINICIANS AND PROVIDERS

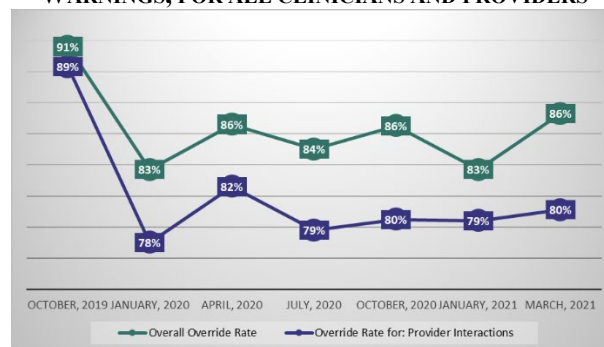


FIGURE 4. TOTAL OVERRIDE RATES OF ALL BPA WARNINGS (OMITTING DRUG-ALLERGY CATEGORY)

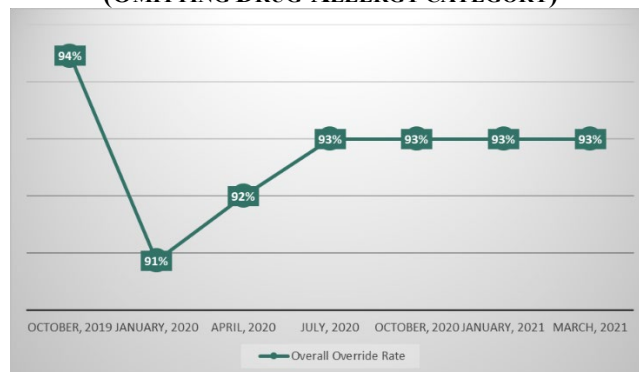


FIGURE 5. KEY OUTCOME MEASURES OF WARNINGS PER 100 ORDERS (INCLUDING EPIC LAUNCH)

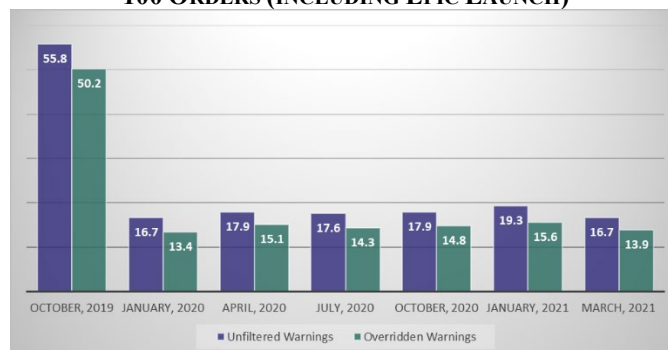


FIGURE 6. KEY OUTCOME MEASURES OF WARNINGS PER 100 ORDERS (OMITTING EPIC LAUNCH)



FIGURE 7: SPECIFIC MEDICATIONS IDENTIFIED CONTRIBUTING THE HIGHEST FREQUENCIES OF ALERTS

Yellow Highlight: High "Number of Unfiltered Warnings" (>200) Descending order of (Column O). Fourteen drugs identified that have a total of 4801 Unfiltered Warnings. Of this list, twelve of these drugs are also the highest number of overridden warnings (column D) total of 3509 overrides. The two bulleted and bold falls into the top 25 and contribute 268 overrides as well.

- OXYCODONE 5 MG TABLET [10814]**
- HYDROMORPHONE 1 MG-ML INJECTION SYRINGE [3757]**
- PROMETHAZINE 25 MG-ML INJECTION SOLUTION [6618]**
- ONDANSETRON HCL (PF) 4 MG-2 ML INJECTION SOLUTION [106348]**
- FENTANYL (PF) 50 MCG-ML INJECTION SOLUTION [131632]**
- HYDROCODONE 5 MG-ACETAMINOPHEN 325 MG TABLET [34505]**
- KETOROLAC 15 MG-ML INJECTION SOLUTION [22472]**
- ACETAMINOPHEN 325 MG TABLET [101]**
- ENOXAPARIN 40 MG-0.4 ML SUBCUTANEOUS SYRINGE [105900]**
- MORPHINE 2 MG-ML INTRAVENOUS SYRINGE [164901]**
- IBUPROFEN 600 MG TABLET [3844]**
- ONDANSETRON 4 MG DISINTEGRATING TABLET [27697]**
- PROMETHAZINE 25 MG TABLET [6622]**
- CEFAZOLIN 2 GRAM/100 ML IN DEXTROSE 5 % INTRAVENOUS SOLUTION [160218]**

Blue Highlight: Highest "Overridden Warnings per Order" (= or > 5 per order, descending column F). Seventeen different drugs identified, total of 412 Unfiltered Warnings 400 of which are overridden.

- VORTIOXETINE 20 MG TABLET [124538]**
- ZIPRASIDONE 20 MG CAPSULE [29778]**
- FLUCONAZOLE 400 MG-200 ML IN SOD. CHLORIDE(ISO) INTRAVENOUS PIGGYBACK [10050]**
- OXYCODONE 10 MG-0.5 ML ORAL SYRINGE (FOR ORAL USE ONLY) [134092]**
- METHADONE 5 MG-5 ML ORAL SOLUTION [4952]**
- PYRIDOSTIGMINE BROMIDE 60 MG TABLET [11239]**
- HALOPERIDOL 5 MG TABLET [3583]**
- TIZANIDINE 2 MG CAPSULE [41086]**
- METHYLERGONOVINE 0.2 MG TABLET [10572]**
- AMPICILLIN 500 MG CAPSULE [466]**
- FLUCONAZOLE 100 MG TABLET [10044]**
- ZIPRASIDONE 40 MG CAPSULE [29779]**
- WARFARIN 7.5 MG TABLET [8752]**
- OXALIPLATIN 100 MG-20 ML INTRAVENOUS SOLUTION [99612]**
- FENTANYL (PF) 10 MCG-ML IN 0.9 % SODIUM CHLORIDE INTRAVENOUS [30807]**
- WARFARIN 2 MG TABLET [8749]**
- METHADONE 10 MG TABLET [4953]**
- CHLORPROMAZINE 25 MG TABLET [1656]**
- MEMANTINE ER 28 MG-DONEPEZIL 10 MG CAPSULE EXT.RELEASE 24 HR [127881]**

FIGURE 8: FINAL RECOMMENDATION: USER-FILTERED WARNINGS TOOL PROMOTION

User-Filtered Warning Promotion Plan:

1. Strategize about leadership and physician buy-in. Including, an understanding why utilization is low, why this is an effective and efficient solution, and how to convey UFW will improve workflow to the end-user.
2. Review the current UFW tool, is this an easy tool to use? How can it be improved? Consider informal surveying of physician input. One improvement could be removing UFW expirations.
3. Revise/edit the materials to ensure the most concise messaging, complemented with supplemental information if necessary.
4. Identify the most effective route for promotion (input from Dr. Whitting). Then make a plan for dissemination.
5. Create a feedback loop and monitor progress with objective metrics.

Pros	Cons
<ul style="list-style-type: none"> • Mitigates system-level liability • Useful functionality • Efficient impact and use of resources (straightforward and easily available) • Caters to specialty of physicians and their preferences • Could be useful in other areas (i.e., a document with physician on-boarding) 	<ul style="list-style-type: none"> • Need physician buy-in • More administrative pressure on physicians • Could require additional research on functionality

UFW example below: Consider how effective UFW suppression would be for an OBGYN physician with this lactation warning. OBGYN physicians would be well aware of whether or not their patients are pregnant/lactating, so this warning is low value for them. However, this warning is high value for other physicians and would create liability if suppressed at a system level. This caters to physician preference and directly addresses the complexity of medical treatment across different specialties.

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